Replies to Referee 1

Bernard and co-authors' manuscript is a concise, clear description of an updated version of the well-known GIEMS inundation product called GIEMS-MethaneCentric (GIEMS-MC). Modifications include separating the areas of open water using the Global Lakes and Wetlands Database version 2 (GLWDv2) and rice paddies from wetland areas, and using filters for coastal zones to avoid ocean artifacts and for regions with snow cover. GIEMS-MC spans the period 1992-2020 on a monthly timescale at 0.25° x 0.25° spatial resolution, and includes one time-series of flooded and saturated wetlands and one for wetlands and peatlands, plus static areas of lakes, rivers and reservoirs, seasonal rice paddies and dominant vegetation. The updated product is compared with the Wetland Area and Dynamics for Methane Modeling (WAD2M) product globally. Regional comparisons are also done for the Siberian Lowlands, the Sudd, the Amazon and South-East Asia. GIEMS-MC is likely to be used by global and regional modeling efforts and should improve estimates of temporal variations in wetland emissions of methane.

Thank you for reviewing this manuscript and for your suggestions that have improved this study. Below you will find point-by-point responses to your comments, together with the corresponding changes made to the new version of the manuscript.

Although the authors state that quantification of the uncertainties of the GIEMS-MC variables is beyond the scope of this study, several aspects of the approach and its validation are in need of further information.

Though the remote sensing basis and limitations of GIEMS and GIEMS-2 are described in a series of publications, a brief summary of these two items would benefit readers of this report.

The description of GIEMS and GIEMS-2 have been modified to be more explicit about these points (lines 102-128 of the track changes document):

"The GIEMS-2 dataset, spanning 1992 to 2015 and extended to 2020 in this study, provides monthly global maps of surface water extent with a spatial resolution of 0.25°x0.25° (Prigent et al., 2020). GIEMS-2 includes all continental water surfaces, such as wetlands, rice paddies, rivers, reservoirs, and lakes, but excludes large lakes > 15 000 km². The original GIEMS-1 methodology (Prigent et al., 2001, 2007; Papa et al., 2006; Prigent et al., 2007; Papa et al., 2008, 2010) and the GIEMS-2 algorithm (Prigent et al., 2020; Bernard et al., 2024b) have been extensively evaluated against other observational products, demonstrating robust capture of seasonal and inter-annual variability, despite uncertainties in wetland extent between currently available products. GIEMS-2 relies primarily on inter-calibrated passive microwave observations from the SSM/I and SSMIS satellites (Fennig et al., 2020) at frequencies from 19 to 85 GHz. The microwave signal is influenced by atmospheric conditions (e.g., water vapor, clouds) and surface variables (e.g., surface temperature, vegetation, snow). Microwave observations are complemented by ancillary information other to limit these artifacts, as described in Prigent et al., (2020). Specifically, active microwave satellite data and Normalised Difference Vegetation Index (NDVI) derived from visible and near-infrared measurements are used to characterize vegetation and mitigate its influence on the passive microwave signal. Since snow

contamination prevents the calculation of surface water, snow-covered pixels (as defined by meteorological reanalysis), are assigned a water fraction of 0 in the previous studies and in the distributed GIEMS-2 product. Passive microwaves are sensitive to the presence of water, including estuarine and offshore marine waters. To avoid misinterpretation of the data, coastal pixels were filtered out in the distributed GIEMS-2 product, leading to a possible underestimation of inundated surface extent in the coastal areas. Here we use an unfiltered version of GIEMS-2 in which coastal regions are not excluded, in order to improve the coastal cleaning process during the production of GIEMS-MC based on GLWDv2, as described in Sect. 3."

The comparisons of WAD2M and GIEMS-MC are primary illustrated in coarse global figures and in a table. Statistical analyses of global and regional differences between these products is needed. The figures showing temporal variability also need quantitative analysis and comparison with other products, when possible.

In order to do statistical analysis of WAD2M and GIEMS-MC spatial patterns, we calculated spatial correlation coefficients between the two datasets, in terms of MAmax and MAmin, at continental and basin scales. Spatial correlation is defined as the pixel-by-pixel correlation between two maps, considering a specific unmasked region.

	Correlation of MAmax		Correlation of MAmin
	WAD2M	**BAWLD**	**WAD2M**
Global	0.61	NaN	0.59
Africa	0.70	NaN	0.76
Europe+Siberia	0.62	NaN	0.12
Asia	0.37	NaN	0.40
Oceania	0.63	NaN	0.62
South America	0.73	NaN	0.66
North America	0.61	NaN	0.49
Sudd	0.71	NaN	0.76
Ob	0.80	0.74	-0.01
Amazon	0.77	NaN	0.71
Congo	0.89	NaN	0.88
South East Asia	0.67	NaN	0.72

We included global and basin metrics into the manuscript text in relevant sections 4.1 and 4.2, along with its definition line 288 of the Track change manuscript. We also added the MAmax and MAmin values of the different datasets over selected basins directly on the Figures (4 to 7), and added it in the relevant paragraphs to use more quantitative metrics.

We do not include more comparison with other surface water products, as we are here interested in wetland products. The extended GIEMS-2 dataset, which detects all surface waters, was compared over 10 basins to other surface water extent products (CYGNSS, MODIS) and river discharge time series in Bernard et al., 2024 (https://doi.org/10.3389/frsen.2024.1399234). This is mentioned in the manuscript lines 111-114 of the track changes document.

The use of GLWDv2 to separate lake, river and reservoir areas is reasonable for many regions, but not for the widespread and extensive floodplains of tropical and northern rivers because open water areas in these systems vary considerably on a seasonal timescale. A discussion of the consequences of this issue should be added.

We do understand your concern about floodplains that have a seasonal variability not represented in the static maps depicted in GLWDv2. However, only permanent open waters (lakes, rivers*, reservoir, estuaries, and deltas) are removed (separated) from GIEMS-2 using GLWD2. Floodplain ecosystems are included in other GLWDv2 classes (10 to 15) and are therefore retained in GIEMS-2 when constructing GIEMS-MC. This has been explicitly added in the manuscript (lines 215 to 216 of the track changes document):

"Note that the floodplain ecosystems are included in other GLWDv2 classes (10 to 15) and are therefore retained in GIEMS-2 when constructing GIEMS-MC."

*Rivers in GLWDv2 are mainly derived from the Global River Width from Landsat (GRWL) dataset (Allen and Pavelsky, 2018), where they are derived during months of average discharge (mean discharge ± one standard deviation, supplement of Allen and Pavelsky, 2018).

The regional comparison for the Amazon basin should mention the evaluation of several inundation products published in Fleischmann et al. (2022). How much inundation occurs in the Amazon River basin? Remote Sensing of Environment. 278, 113099. doi.org/10.1016/j.rse.2022.113099. Given the limitations of the sensors used by GIEMS and the well-validated results from synthetic aperture radar in seasonally inundated forests, this publication provides valuable information about some of the uncertainties inherent in the GIEMS products.

We added a reference to this study (lines 337 to 343 of the track changes document), in particular the extent found by the SAR estimates, highlighting also that wetland and inundated extent are different:

"Over the Amazon (Fig. 6), GIEMS-MC$_{ISW}$ fractions are high (>0.5) along the main river channel, while including peatlands adds smaller surfaces along smaller secondary channels, resulting in finer spatial patterns and higher MAmax (0.31 to 0.56 Mkm2). The resulting GIEMS-MC$_{ISW+P}$ MAmax map closely resembles that of WAD2M (spatial correlation coefficient of 0.77), with a slightly higher MAmax for WAD2M (0.47 Mkm²). GIEMS-MC$_{ISW}$ extent can be potentially underestimated in this basin, as Fleischmann et al. (2022) found that GIEMS-2 estimates of inundation were likely slightly underestimated compared to higher resolution remote sensing estimates based on Synthetic Aperture Radar (SAR), with Chapman et al. (2015) finding +4% and Rosenqvist et al. (2020) +36% compared to GIEMS-2 long term maximum inundation."

The Boreal–Arctic Wetland and Lake Dataset (BAWLD) would seem appropriate for comparison in northern regions.

We thank the reviewer for this suggestion. We added BAWLD in the Figure comparison over the Ob basin (Fig. 4), and its comparison within the text (lines 322 to 326 of the track changes document):

"The Boreal-Arctic Wetland and Lake Dataset (BAWLD) is also shown for comparison, as it covers the upper part of the basin (Olefeldt et al., 2021b, a). The BAWLD wetland fraction, including peatland classes, exhibits patterns similar to GIEMS-MC$_{ISW+P}$ MAmax, with a spatial correlation coefficient of 0.74. However, BAWLD covers a slightly larger area (+6%) compared to the GIEMS-MC$_{ISW+P}$ MAmax when comparing the common area covered by the two datasets."

Given that peatlands add a large area to the GIEMS-MC results, an evaluation of the veracity of the peatland products is needed. For example, the approach used by Gumbricht et al. (2017) has serious problems, at least for the Amazon basin. In general, remote sensing of peatlands is difficult.

Peatlands have been the focus of numerous studies in recent years (Gumbricht et al., 2017; Xu et al., 2018; Melton et al., 2022; Global Peatland Map 2.0, 2022; Minasny et al., 2024), with multiple questions about the accuracy and evaluation of existing datasets. We added a paragraph in the section 5.2.3 Peatland integration to discuss this (lines 478 to 487 of the track changes document) :

"Non-inundated peatlands account for a significant proportion of the GIEMS-MC$_{ISW+P}$ in terms of maximum area (50.2% of the MAmax, see Table 2). The peatland map used in this study to derive GIEMS-MC$_{ISW+P}$ comes from GLWDv2, and is a composite product based on four different estimates (see section 3.1.7 or Lehner et al. (2024a)). It should be emphasized that although this product is based on the best current knowledge, there is still limited consensus in the literature on the extent of peatlands. Mapping of peatlands remains challenging, as it is primarily a soil characteristic related to organic carbon content that cannot be directly detected by satellite data. Consequently, mapping efforts rely on approaches based on observations (in situ data and / or remote sensing proxies for, e.g., vegetation or hydrological data) to map their extent using models or machine learning. This task is particularly difficult in tropical regions, where in situ data are sparse and where dense cloud and vegetation covers limit remote sensing observations. This results in fewer regional maps over the Tropics with frequent revisions towards higher estimates of tropical peatland areas (Dargie et al., 2017; Hastie et al., 2024)."

Though the ERA product provides a global estimate of the occurrence of snowcover, a comparison of these estimates with the SNODAS products for parts of North America or with other snowcover products would be useful.

Note: As Referee 2 asked a similar question, we have given the same answer to both reviewers.

The ERA5 snow mask is used in the production of GIEMS-2, and for consistency, we applied the same mask in GIEMS-MC. ERA5 offers the advantage of global coverage and an uninterrupted long-term record (from 1970 to the present, with ongoing updates). In our processing, ERA5 snow data is used to filter out pixels affected by snow, as snow has complex and highly variable behavior in passive microwave observations, which are used to estimate surface water. The goal is to prevent any contamination of surface water estimates by snow.

Our approach is deliberately conservative in identifying snow-covered areas, which may result in missing some regions near the snow margin. Yet, this is expected to have minimal impact on global methane emission estimates, as temperatures in these areas are typically low (close to 0°C).

We acknowledge that ERA5 snow cover is not a perfect dataset. However, it has been found to be more consistent in terms of trends than, for instance, the NOAA CDR reanalysis product (Urraca et al., 2023). ERA5 effectively captures interannual variations (Kouki et al., 2023), and after 2004, it has been shown to provide the highest accuracy compared to ground measurements among available datasets (Urraca et al., 2023). Some discontinuities in the time series have been reported, particularly around 2004 (Urraca et al., 2023). However, we verified that this does not impact GIEMS-MC surface water extent in northern basins where the snow mask has the greatest influence. For example, no discontinuity is observed in 2004 in the Ob basin, as illustrated in Figure 9 of the paper. It is worth noting that ERA5 generally estimates a larger snow cover extent than other datasets, primarily due to higher values in mountainous regions (Kouki et al., 2023). However, these regions are also poorly represented in other long-term datasets, including remote sensing products (Bormann et al., 2018).

We added in section *2.4 Snow-covered pixel masking* of the manuscript a paragraph to discuss the snow mask importance (lines 498 to 503 of the track changes document):

"For consistency with the snow mask used in GIEMS-2 production, we have used the same mask here in the GIEMS-MC generation. This mask is derived from the ERA5 product, which might overestimate the extent of snow cover but still captures interannual changes well (Kouki et al., 2023). The snow mask in GIEMS-MC is only a filter for pixels potentially contaminated by the presence of snow. The potential overestimation of snow cover extent should have limited implications for methane emissions, as methane emissions in these regions during the snow season should be a small fraction of global emissions, as discussed above."

The European Space Agency Land Cover dataset has limitations when applied to seasonally varying wetland vegetation, and these uncertainties need to be mentioned.

Here, the ESA Land Cover dataset is used to estimate vegetation types for potential application in methane emission modeling (only the main vegetation type is provided, as an indicator, per 0.25°x0.25° pixel). Studies have shown that vegetation type highly influences methane emissions in wetland areas (Pangala et al., 2017; Vroom et al., 2022; Ge et al., 2024; Feron et al., 2024; Girkin et al., 2025). To support this, GIEMS-MC provides a vegetation and wetland type information, enabling potential refinement of methane emission parameterization based on vegetation characteristics. ERA5 CCI LC product has its limitations, but here only a yearly value at low resolution is given as indicator, the seasonal and inter-annual changes are not taken into account.